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Adult Age Differences and the Role of Cognitive Resources in Perceptual–Motor Skill Acquisition: Application of a Multilevel Negative Exponential Model

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The effects of advanced age and cognitive resources on the course of skill acquisition are unclear, and discrepancies among studies may reflect limitations of data analytic approaches. We applied a multilevel negative exponential model to skill acquisition data from 80 trials (four 20-trial blocks) of a pursuit rotor task administered to healthy adults (19–80 years old). The analyses conducted at the single-trial level indicated that the negative exponential function described performance well. Learning parameters correlated with measures of task-relevant cognitive resources on all blocks except the last and with age on all blocks after the second. Thus, age differences in motor skill acquisition may evolve in 2 phases: In the first, age differences are collinear with individual differences in task-relevant cognitive resources; in the second, age differences orthogonal to these resources emerge.

Key Words: Aging—Motor performance—Multilevel model—Negative exponential learning function—Pursuit rotor—Skill acquisition—Working memory.

ADVANCED age is associated with declines in cognitive performance. At the same time, it is frequently assumed that some aspects of cognitive performance such as earlier acquired procedural skills, are relatively age invariant (e.g., Nilsson, 2003). Recent findings suggest, however, that at least some procedural skills are not immune to the influence of aging. Even in healthy adults, age-related decrements occur on classic perceptual–motor tasks, such as pursuit rotor (PR; Brosseau, Potvin, & Rouleau, 2007; Durkin, Prescott, Furchtgott, Cantor, & Powell, 1990; Raz, Williamson, Gunning-Dixon, Head, & Acker, 2000).

In many cognitive domains, adult age differences reflect differential availability of resources measured by working memory (WM) capacity (Craik & Byrd, 1982) or various aspects of executive functions (Dempster, 1992). Of relevance here, age differences in acquisition or maintenance of some skills correlate with those in cognitive resources (Kennedy, Partridge, & Raz, 2008; Kennedy & Raz, 2005; Kennedy, Rodrigue, & Raz, 2007) and may reflect difficulties in meeting the executive demands of the task (Bock, 2005). Moreover, aging effects on motor performance may be mediated by WM deficits (Maylor & Wing, 1996). Although it is not clear how WM affects motor learning, it provides resources for mental imagery (Kosslyn, 1994) that in turn serves as an important predictor of motor skill acquisition (Jeannerod, 1994). Therefore, it is desirable to identify age-associated variables such as cognitive resources that capture mechanisms of individual differences in skill acquisition more directly.

Some studies have reported that the shape of acquisition trajectories is age invariant, with an age-associated shift to lower performance levels (Durkin et al., 1990). Other studies, conversely, point to adult age differences in the rate of skill acquisition. When the target of pursuit follows a regular predictable path, skill learning is slower in older adults (Wright & Payne, 1985). Moreover, older adults show a shallower approach to asymptotic levels than their younger counterparts (Raz et al., 2000).

Skill acquisition process is not uniform. Rapid initial stage of learning brings marked improvement, whereas the second slow stage yields only minor incremental gains (Karni & Bertini, 1997; Karni & Sagi, 1993). Thus, aging may differentially affect specific stages of the acquisition process, and the magnitude of age differences may depend on the specific demands that characterize every stage. Such differential response of skill acquisition to age-related changes may reflect the extent to which the task calls upon brain substrates of learning that are differentially affected by aging (see Doyon, Penhune, & Ungerleider, 2003 for a review).

Thus, to understand age-related differences in skill acquisition, it is important to identify the distinct stages of learning, to examine their characteristic learning trajectories, and to determine which of the learning stages and the within-stage parameters of skill acquisition show age-related variability and whether and how they are associated with cognitive resources. Reliable identification and isolation of stages and parameters of learning depend on the choice of appropriate methodological designs and statistical tools,

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and to date, reliance on ordinary least squares linear models might have hampered the progress in that area. The search for an optimal statistical apparatus that would fit that substantive area is in the focus of this investigation.

Level of analysis and statistical approaches

In a study of age differences, two methodological issues are particularly salient: the level of analysis and the statistical approach. Concerning the former, the study of age effects in skill acquisition may be sensitive to the extent of data aggregation and selection of units of measurement, scaling, and analytic approach. A trial-by-trial analysis may establish clearer relations between level of performance and skill acquisition and their associations with age and cognitive resources than an analysis where data are aggregated across trials (e.g., Lövdén, Li, Shing, & Lindenberger, 2007). To capture the fine structure of a rapidly changing learning process, data should be modeled at the trial level rather than at the level of multitrial aggregates.

Concerning the second methodological issue, several statistical approaches to analyze individual differences in learning data have been proposed and implemented independently of the specific interest in age-related differences. A desirable analytical procedure requires specification of a model believed to characterize the learning process at both the sample and the individual level. However, such a model should be able to faithfully reflect the fine trial-by-trial structure as discussed earlier. To satisfy that requirement, a procedure should estimate parameters that characterize the individual acquisition trajectories. Moreover, such trajectories, in addition to reliably fitting the data, should be interpretable in terms of skill acquisition theories. One such analytical procedure is the multilevel model (MLM; Bryk & Raudenbush, 1987; Goldstein, 1989). That approach allows analyzing inherently hierarchical data in which each level constitutes a source of variability. A classical application of MLM is a repeated measures structure, where the variable of interest is directly influenced by time (the repeated measurements at the first level of the hierarchy) and by individual characteristics (at the second level). The usefulness of MLM to elucidating learning processes in experimental settings has been shown before (e.g., MacDonald, Stigsdotter-Neely, Derwinger, & Bäckman, 2006; Yeo & Neal, 2004). Within the MLM framework, various mathematical functions, each corresponding to different theories of skill acquisition, can be applied to modeling of the learning process (e.g., Browne & Du Toit, 1991; Newell & Rosenbloom, 1981). The negative exponential function (Meredith & Tisak, 1990) formally describes learning processes with significant explicit components (Blozis, 2004; Meredith & Tisak; Newell & Rosenbloom; Parasuraman & Giambra, 1991; Zimprich, Rast, & Martin, 2008). The three main parameters of the negative exponential function represent the initial performance level, the learning rate, and the final attainable performance level. Within the MLM, the three components may characterize the sample trajectory (through their means or fixed effects) as well as individual deviations around the sample trajectory (through their variances or random effects). Furthermore, the individual deviations can then be conditioned upon covariates. In sum, the negative exponential function implemented as an MLM on single-trial data provides a promising analytical tool for testing hypotheses about the functional heterogeneity of learning trajectories and their relations to chronological age and cognitive resources.

Objectives

The first goals of this study were to examine the shape of acquisition curves at various stages of learning, to derive the best-fitting parameter values of the negative exponential function describing the process at each stage, and to determine which of these parameters are more prone to show age differences. We focus not only on this function because of the theoretical relevance of its three components but also on empirical grounds. Indeed, previous analyses (not reported here) compared the following growth shapes: linear, linear and quadratic, logistic, free basis, and the negative exponential. This last function consistently provided the most satisfactory compromise between statistical fit to the data of each block and theoretical interpretation of its parameters, and for the sake of simplicity, it is the only function presented here. We implement the negative exponential function as an MLM. To the best of our knowledge, this approach has not yet been applied to investigate adult age differences in perceptual–motor skill acquisition. The second goal of this study was to determine the extent to which age differences depend on other factors. Specifically, we investigated whether cognitive resources modify the age-conditioned parameters of skill acquisition curves. With these two goals in mind, we hope to elucidate the factors that affect skill acquisition processes.

To attain our objectives, we reanalyzed the PR data reported in Kennedy and colleagues (2008) using MLM, with addition of a few participants, whose data were not complete and not analyzed before. In that study, the PR task was administered in four blocks of 20 trials each. Within each block, we applied the negative exponential function to single-trial data, both at the sample and at the individual level, to examine the relations between the learning parameters across the different blocks. To further understand the role of reduced cognitive resources on age-related differences in learning, we extended the analysis by examining the effects of age and of cognitive resource variables on the learning parameters.

Methods

Participants

The sample consisted of 102 participants (*M* age = 47.63 years, *SD* = 17.16, range = 19–80) recruited in the Memphis metropolitan area by advertising in local media and on the University of Memphis campus. The distribution by age decades was as follows: 19–29 years of age $n = 21$, 30–39 $n = 13$, 40–49 $n = 18$, 50–59 $n = 19$, 60–69 $n = 22$, and 70–80$n = 9$). Sixty (59%) participants were women, 14 (14%) were African American, and 88 were Caucasian. To screen the participants for history of neurological, psychiatric, and medical conditions, including history of diabetes and thyroid disorders, head trauma with loss of consciousness, and alcohol and drug abuse, we used a health questionnaire and interviewed the participants via telephone and in person. Due to sensory and motor demands of the task, we also excluded participants with arthritis and sensory deficiencies. Eleven (10%) participants had a diagnosis of hypertension and were taking medications. All participants were right-handed (with a score of 75% or greater on the Edinburgh Handedness Questionnaire; Oldfield, 1971) and native English speakers. They were screened for dementia with the Blessed Information-Memory-Concentration Test (cutoff of 30; Blessed, Tomlinson, & Roth, 1968) and for depression with the Geriatric Depression Questionnaire (cutoff of 15; Radloff, 1977). The minimum formal education was set at high school degree level, and on average, participants had 4 years of college education (16.02 ± 2.57 years of formal education).

Perceptual–Motor Skills

Participants performed the PR task implemented on a standard photoelectric PR apparatus (Model 30014; Lafayette Instruments, Lafayette, IN). Participants had to keep a J-shaped wand held in their dominant (right) hand over a rotating light spot while standing in front of the apparatus (the height of the light table was adjusted for each participant). On each trial, the time on target was automatically measured by the apparatus, and the total time on target in seconds served as the main index of performance.

Participants were tested individually during four blocks of 20 trials each, on three consecutive days, for a total of 80 trials. On the first, second, and third day, there were, respectively, two, one, and one block of twenty 15-s trials. There was a 10-s intertrial rest. Ninety-three participants were assessed on all days (for 80 trials), 6 only on Days 1 and 2 (60 trials), and 6 only on Day 1 (40 trials).

Cognitive Resources

To measure age-related differences in cognitive resources, we administered several WM tasks. Two verbal WM tasks were Listening Span and Computation Span (LS and CS, respectively; Salthouse, Mitchell, Skovronek, & Babcock, 1990). In the LS task, participants listened to simple sentences, were asked a question about their content, and finally were asked to recall the last word of each. In the CS task, participants were to solve simple arithmetic problems and to remember the last digit of each. The number of items (sentences or problems) ranged from one to seven, and all items were presented to all participants in groups of three. Of the three scores available for each span task, we used the absolute score.

Two nonverbal WM tasks were also administered: Size Judgment Span (SJS) and Spatial Relations (SR). In the SJS task, modified after Cherry and Park (1993), participants listened to a list of objects or animals and had to recall them in ascending size order. Lists started with two items and were incremented according to participants' performance. The total number of correct responses was the index of performance. The SR task is a subtest in the Woodcock–Johnson Psycho-Educational Battery–Revised (Woodcock & Johnson, 1989) and exerts considerable demands on WM besides spatial abilities. Indeed, participants are presented with a whole shape as well as with a series of six disjointed shapes from which they are asked to choose a correct combination. The complexity and degree of abstraction of the shapes augment according to participants' capacities. The total number of correct responses was analyzed.

Finally, to assess additional executive functions, we administered the Wisconsin Card Sorting Task (WCST; Neuroscan Corp., Herndon, VA; Heaton, Chelune, Talley, Kay, & Curtis, 1993). Participants observed a deck of stimulus cards on a computer screen and then a stack of additional cards, which they were asked to match singularly to the stimulus cards. Participants were not told the matching rule, only whether their match was correct or not. The number of perseverative errors served as the performance index on that task (cf. Greve, Stickle, Love, Bianchini, & Stanford, 2005).

To facilitate parameter interpretation, all cognitive scores and age were centered on their grand mean. More detail about the cognitive tasks can be found in previous published works (Kennedy et al., 2007, 2008; Raz et al., 2000).

The Multilevel Negative Exponential Model

We tested the negative exponential learning function within the MLM to describe the participants' longitudinal learning trajectories across all trials. The function characterizes individuals on the basis of three specific components of interest: initial performance (α), acquisition rate (γ), and final performance (β; Meredith & Tisak, 1990). We had to expand this function to the dual negative exponential model (e.g., McArdle, Ferrer-Caja, Hamagami, & Woodcock, 2002), which further includes a parameter δ to model the decline rate evident toward the second half of Block 2 (for more details, see subsequently). We estimated both a fixed and a random effect for each component. Fixed effects are equivalent to means and represent sample characteristics. Random effects are equivalent to variances around the fixed effects and characterize individual deviations from the sample. The model also estimated the degree of linear relations between the learning components, and these are represented by covariances.

Table 1. Parameter Estimates and Standard Errors of Analysis Without Statistical Control for Age and Cognitive Resources

	Fixed effects				Random effects			
Block	α	γ	δ	β	α	γ	δ	β
1	2.855 (0.225)	0.336 (0.029)	—	5.759 (0.230)	2.863 (0.489)	0.070 (0.019)	—	3.806 (0.551)
2	4.430 (0.489)	0.525 (0.137)	0.100 (0.025)	6.461 (0.248)	*10.222 (9.903)*	*0.031 (0.454)*	*0.034 (0.038)*	3.638 (0.846)
3	7.448 (0.258)	0.297 (0.046)	—	7.946 (0.242)	4.169 (0.679)	*1.269 (0.816)*	—	4.125 (0.602)
4	8.282 (0.233)	0.228 (0.042)	—	8.362 (0.233)	3.473 (0.574)	*48.065 (162.757)*	—	3.992 (0.612)

Notes: The fit indices of this model were $\chi^2(df = 3{,}136, N = 102) = 5{,}630.108$, RMSEA = .088 (90% CI = [.085–.092]), SRMR = .038, and CFI = .828. Parameters are presented with point estimates and, in parentheses, standard errors. α (initial performance), γ (acquisition rate), δ (decline rate), and β (final performance) are the parameters of the negative exponential function. Italicized numbers refer to statistically nonsignificant parameter estimates. RMSEA = root mean square error of approximation; CI = confidence interval; SRMR = standardized root mean square residual; CFI = comparative fit index.

Equation (1) represents the dual negative exponential function, which posits that the performance Y at trial t for individual i is dependent on an initial level α, a rate of growth γ, a rate of decline δ, a final upper asymptote β, and a residual term $r_{t,i}$.

$$Y_{t,i} = \beta_i - (\beta_i - \alpha_i) \cdot \left(e^{-\gamma_i \cdot (t_{t,i}-1)} - e^{-\delta_i \cdot (t_{t,i}-1)} \right) + r_{t,i} \qquad (1)$$

The mean and variance of α, γ, δ, and β and their six covariances were estimated. The negative exponential model is obtained by omitting the exponential term with the decline parameter δ and is appropriate when the trend is monotonously increasing (Appendix, Note 1).

General modeling procedure.—The dual negative exponential model was only applied to Block 2, where the simpler version was unable to account for the decreasing final performances. In all other blocks, the decline parameter δ was not necessary. The analyses were implemented with the M*plus* software (version 5; Muthén & Muthén, 1998–2007; Appendix, Note 2). This is possible because the (dual) negative exponential function is nonlinear in the fixed effects but linear in the random effects. It is, however, necessary to enforce particular constraints on the fixed parameters (for more information, cf. Blozis, 2004, 2007; Blozis, Conger, & Harring, 2007; Browne, 1993; see the Supplementary Appendix for the scripts).

The data of the 12 participants who were not assessed on all 80 trials (<2% of the total data) were included in the analyses, and all parameters were obtained by means of maximum likelihood estimation. This technique is very easily applied with current software and avoids both the exclusion and the replacement of cases with incomplete data while estimating unbiased parameters under typical testing conditions (Schafer & Graham, 2002).

We combined the data of the four blocks into a single analysis to study the relationships among the learning components across all 80 trials (MacCallum, Kim, Malarkey, & Kiecolt-Glaser, 1997). The learning components of the four blocks were allowed to intercorrelate. In the end, we obtained a correlation matrix with the learning components of all four blocks to assess the degree of generality in the acquisition of perceptual–motor skills across all trials. This analysis was performed first without and then with the inclusion of age and cognitive resources as covariates.

The residuals were not allowed to correlate with time and followed an unstructured diagonal matrix. Within each block, we tested whether the residual variance was constant or changed across trials (structured vs. unstructured diagonal matrix) and found the latter to be true in all blocks.

Results

To evaluate the goodness of fit of the negative exponential function, we rely on the χ^2 statistic with its degrees of freedom, the root mean square error of approximation (RMSEA) with its 90% confidence interval (CI; Browne & Cudeck, 1993), the standardized root mean square residual (SRMR), and the comparative fit index (CFI). Generally, an RMSEA value of 0 indicates an excellent fit of the model to the data, less than .05 a close fit, less than .10 a mediocre fit, and greater than .10 a poor fit. If its CI includes .05, one can conclude a close fit. In general, an SRMR inferior to .05 and a CFI superior to .95 indicate a very good fit.

Analysis Without Statistical Control for Age and Cognitive Resources

The analysis without age and cognitive resources provided an acceptable fit to the data (RMSEA = .088, SRMR = .038, and CFI = .828). On average, 82.40% of the variance of time-on-target performance of all 80 trials was explained by the learning components of the negative exponential function, indicating the appropriateness of this data analytical approach.

The parameter estimates of this model appear in Table 1. The first column specifies the block. Next, the fixed effects of α, β, γ, and δ are presented, followed by their random effects. Random effects of the residuals ($r_{t,i}$) are not presented to reduce the size of the tables (these estimates are secondary to the understanding of the learning process, and no systematic or anomalous estimates were obtained). On average, the predicted initial performance (α of Block 1) was poor, with the average time on target of only 2.86 s. Performance improved exponentially and at the end of the

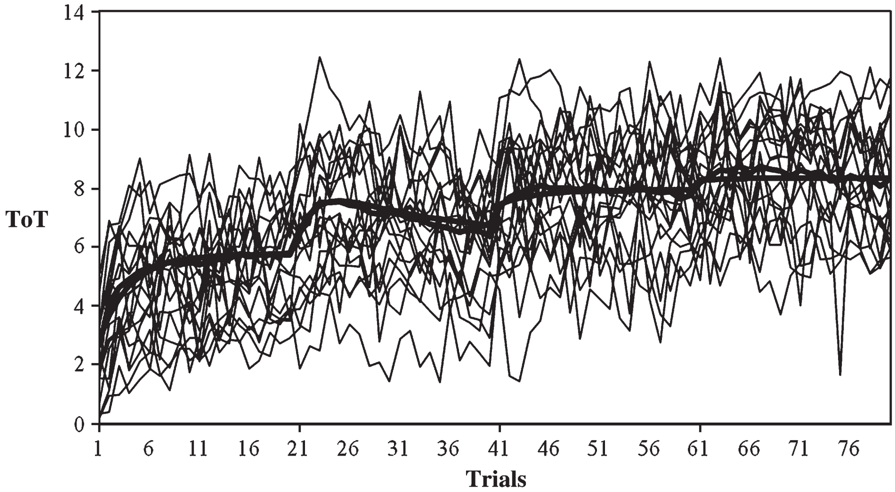

Figure 1. Complete longitudinal trajectories over the 80 trials on pursuit rotor performance measured as time on target (ToT) in seconds for a random subsample (n = 20). The thick jagged line and the thick smooth line represent the empirical and the predicted average performance curves, respectively.

first block (at Trial 20) reached a predicted average upper asymptote (β) of 5.76 s. The predicted average starting value of the next block was lower, at 4.43, whereas the final performance of Block 2 was higher at 6.46 s. In the third block (Day 2), the predicted average initial and final performances were of 7.45 and 7.95 s, respectively. Finally, in the last block (Day 3), the predicted performance increased from 8.28 to 8.36 s. Note that initial trials on Days 2 and 3 yielded better performance than the final trials on the previous day.

The individual variations around the fixed effects were not negligible and reflect the overall heterogeneity in perceptual–motor skill performance and learning in this sample. On all blocks except the second, the initial performance differed markedly across individuals (cf. random effects of α). Also, participants differed widely with respect to the final performance (i.e., random effects of β). Individual learning rates, however, were not quite as heterogeneous. Indeed, the only random effect of γ that was statistically different from 0 was in the first block. Moreover, its size (0.07) indicates small interindividual differences in motor skill acquisition rate.

Besides showing a random subsample of 20 individual learning curves, Figure 1 also depicts the empirical (thick jagged line) and the predicted (thick smooth line) average learning curves according to the fixed parameters of Table 1. As evident from that display, the two curves are very close across all blocks. In Blocks 1–3, the predicted average curve increases because the decline component δ of the dual negative exponential model was not included. In Block 2, however, the inclusion of δ allowed accounting for the decrease after the fifth trial, most probably due to a combination of boredom and fatigue as Block 2 was the last of Day 1.

Analysis With Statistical Control for Age and Cognitive Resources

The analysis with statistical control for the covariates allowed examining the extent to which individual variations in the learning components were dependent on age and on cognitive resources. The random effects that were significantly different from 0, displayed on the right half of Table 1, indicate that those components of the learning functions varied across participants. In an attempt to explain heterogeneity in learning components, we introduced age and the indices of cognitive resources to the previous MLM to explain random effects of initial and final levels of performance (α and β) and rate of learning (γ) in Blocks 1, 3, and 4 and additionally of decline (δ) in Block 2. The statistical fit of this model was worse than the preceding (RMSEA = .110, SRMR = .064, and CFI = .732). We nevertheless pursued exploring covariate relations, given that the previous model provided an acceptable statistical account of the learning process. Despite the overall fit, the data analytical approach seemed appropriate as on average, 82.36% of the variance of time-on-target performance of all trials was explained by the learning components of the learning functions.

Table 2 shows the parameter estimates of this model in the same order as in Table 1. Because the covariates were centered on their means, the fixed effects virtually did not differ from those obtained in the previous analysis. The addition of age and the cognitive resource indicators led to smaller estimates of interindividual differences because the random effects of Table 2 are residualized for age and cognitive resources. Thus, these covariates did explain some of the previously observed heterogeneity in skill acquisition. Indeed, age and cognitive resources explained 22.33% of the variation in the learning components. This indicates that a good portion of variance remains to be explained (i.e., the

Table 2. Parameter Estimates and Standard Errors of Analysis With Statistical Control for Age and Cognitive Resources

	Fixed effects				Random effects			
Block	α	γ	δ	β	α	γ	δ	β
1	2.901 (0.205)	0.350 (0.031)	—	5.807 (0.199)	2.213 (0.414)	0.067 (0.018)	—	2.836 (0.425)
2	4.390 (0.576)	0.504 (0.126)	0.112 (0.031)	6.527 (0.214)	*11.889 (13.242)*	*−0.270 (0.504)*	*0.026 (0.042)*	2.303 (0.682)
3	7.478 (0.217)	0.303 (0.046)	—	7.972 (0.209)	2.739 (0.487)	*1.255 (0.811)*	—	2.978 (0.446)
4	8.239 (0.193)	0.233 (0.041)	—	8.347 (0.193)	2.053 (0.378)	*24.255 (58.554)*	—	2.626 (0.419)

Notes: The fit indices of this model were $\chi^2(df = 3{,}538, N = 102) = 7{,}927.211$, RMSEA = .110 (90% CI = [.107–.114]), SRMR = .064, and CFI = .732. Parameters are presented with point estimates and, in parentheses, standard errors. α (initial performance), γ (acquisition rate), δ (decline rate), and β (final performance) are the parameters of the negative exponential function. Italicized numbers refer to statistically nonsignificant parameter estimates. RMSEA = root mean square error of approximation; CI = confidence interval; SRMR = standardized root mean square residual; CFI = comparative fit index.

statistical significance of some random effects remained). Standard errors of all random effects also decreased.

Table 3 presents the parameter estimates of the effects (regression weights) of cognitive performance and age on the learning components of each block. The parameter indices refer to the block. Results showed that neither the verbal WM (LS and CS tasks) nor the perseveration index from the WCST predicted learning performance. SJS only predicted final performance in Block 4. In contrast, a higher performance on the SR task predicted better initial performance in Blocks 1 and 3 and greater final time on target in Blocks 1 and 2. The deleterious effects of advanced age were not important until well into the task. Indeed, greater age negatively affected both initial and final performances in Blocks 3 and 4. However, advanced age predicted better learning on Block 1. Although age and cognitive resources together explained 22.33% of individual differences in learning components, their unique contributions were very similar: 4.67% for age and 5.66% for the cognitive resources.

Generality in the Acquisition of Perceptual–Motor Skills Across All Trials

Table 4 presents the correlations among the 13 learning components obtained from the analyses. The above-diagonal numbers are the correlations for the model with age and cognitive resources, whereas the numbers below the diagonal are the correlations of the model without the covariates. The indices of the learning components refer to the block. These correlations are the standardized random effects among all learning components. That is, they represent the degree to which block-specific individual differences in initial and final levels of performance and in rate of learning and decline are related across the four blocks. In both models, there were eight learning components with reliable random effects (cf. Tables 1 and 2). Of these, three represented individual differences in initial performance (α_1, α_3, and α_4), four stood for final level of performance (the four β components), and only one referred to individual differences in learning rate (γ_1). However, to avoid overspecifying the model to the data, we estimated the correlations of all learning components, in

Table 3. Regression Weights (and *SE*s) of the Cognitive Resource Variables and Age in the Prediction of the Learning Components in Each Block

	LS	CS	SJS	SR	WCST	Age
α_1	0.004 (0.018)	0.008 (0.014)	0.165 (0.123)	0.142[a] (0.060)	0.006 (0.010)	−0.006 (0.012)
γ_1	0.003 (0.004)	0.000 (0.003)	0.000 (0.024)	0.007 (0.010)	−0.002 (0.002)	0.006[a] (0.003)
β_1	−0.004 (0.002)	0.002 (0.014)	0.157 (0.129)	0.157[a] (0.057)	0.000 (0.010)	−0.024 (0.013)
α_2	−0.089 (0.146)	0.088 (0.126)	0.007 (0.469)	0.005 (0.235)	−0.002 (0.061)	−0.065 (0.107)
γ_2	−0.029 (0.017)	0.028 (0.013)[b]	−0.017 (0.110)	−0.010 (0.047)	0.013 (0.009)	−0.018 (0.012)
δ_2	0.007 (0.006)	−0.006 (0.004)	0.006 (0.029)	0.012 (0.013)	−0.003 (0.003)	0.005 (0.005)
β_2	0.023 (0.021)	−0.023 (0.015)	0.158 (0.144)	0.167[a] (0.063)	−0.016 (0.012)	−0.013 (0.014)
α_3	0.014 (0.020)	−0.011 (0.015)	0.125 (0.138)	0.149[a] (0.059)	−0.010 (0.011)	−0.034[a] (0.014)
γ_3	−0.008 (0.017)	0.003 (0.012)	−0.019 (0.113)	0.073 (0.052)	0.006 (0.009)	0.002 (0.011)
β_3	0.008 (0.020)	−0.005 (0.014)	0.204 (0.133)	0.116[a] (0.058)	−0.006 (0.011)	−0.028[a] (0.013)
α_4	0.020 (0.018)	0.004 (0.014)	0.175 (0.122)	0.080 (0.055)	0.010 (0.010)	−0.042[a] (0.012)
γ_4	−0.037 (0.084)	−0.025 (0.060)	−0.194 (0.529)	0.392 (0.514)	−0.029 (0.056)	0.053 (0.080)
β_4	0.009 (0.019)	−0.001 (0.014)	0.280[a] (0.127)	0.074 (0.057)	−0.002 (0.010)	−0.033[a] (0.013)

Notes: α (initial performance), γ (acquisition rate), δ (decline rate), and β (final performance) are the parameters of the negative exponential function. Indices refer to the block. LS = Listening Span; CS = Computation Span; SJS = Size Judgment Span; SR = Spatial Relation of Woodcock–Johnson Psycho-Educational Battery–Revised; WCST = Wisconsin Card Sorting Task.

[a] Statistically significant parameters at the $p = .01$ level.

[b] An effect that resulted statistically significant but that must be ignored because it is not defined (given that in the previous model the dependent variable of this effect had no variance).

Table 4. Correlations Among Learning Parameters in Analyses Without or With Predictors in Lower or Upper Diagonal, Respectively

	Block 1			Block 2				Block 3			Block 4		
	α_1	γ_1	β_1	α_2	γ_2	δ_2	β_2	α_3	γ_3	β_3	α_4	γ_4	β_4
α_1	—	−.196	.747[a]	.475	.082	.030	.839[a]	.646[a]	−.041	.642[a]	.651[a]	−.122	.619[a]
γ_1	−.119	—	−.306[a]	−.670[b]	.721[b]	.808	−.169	−.166	−.153	−.169	−.172	.353[b]	−.135
β_1	.801[a]	−.247[a]	—	.457	−.032	−.122	.980[a]	.837[a]	−.083	.830[a]	.793[a]	−.130	.700[a]
α_2	.576	−.555	.566[b]	—	.186	−.881	.517	.391	−.375	.394	.343	−.159	.217
γ_2	.393	−2.361	.084	1.419	—	.227	.318	−.147	−.120	.065	−.062	−.102	−.134
δ_2	.069	.691[b]	−.049	−.714	−1.273	—	−.221	.141	.356	−.029	.185	.247	.133
β_2	.834[a]	−.074	.939[a]	.502	.026	.101	—	1.028[a]	−.128	.943[a]	1.009[a]	−.078	.875[a]
α_3	.707[a]	−.129	.870[a]	.541	−.333	.135	.991[a]	—	−.045	.866[a]	.959[a]	−.119	.782[a]
γ_3	.039	.170	−.024	−.324	−.125	.295	−.066	−.016	—	−.122	.027	.567[b]	−.003
β_3	.711[a]	−.141	.867[a]	.513[b]	.192	.026	.926[a]	.903[a]	−.090	—	.892[a]	−.125	.877[a]
α_4	.706[a]	−.173	.825[a]	.511	.299	.075	.918[a]	.945[a]	.019	.902[a]	—	−.019	.882[a]
γ_4	−.060	.388[b]	−.092	−.145	−.569	.288	−.010	−.092	.570[b]	−.114	−.094	—	−.269
β_4	.685[a]	−.132	.769[a]	.394	−.167	.095	.864[a]	.844[a]	−.016	.909[a]	.912[a]	−.267	—

Notes: α (initial performance), γ (acquisition rate), δ (decline rate), and β (final performance) are the parameters of the negative exponential function. Indices refer to the block.

[a] Statistically significant correlations at the $p = .01$ level.

[b] Correlations that resulted statistically significant but that must be ignored because they are not defined (given that at least one of the two variables being correlated had no variance.

particular also those between the components without statistically significant random effects (α_2, γ_2, γ_3, γ_4, and δ_2). If any of these correlations appear statistically significant, they are ignored because they were not defined.

In the model without covariates, there were 22 statistically significant correlations of a total of 28 defined correlations (representing 79%). All were high, averaging $r = .82$ and ranging from $r = .69$ to .99. The only exception was the correlation between γ_1 and β_1, $r = -.25$. In the model with age and cognitive resources, the same 22 (partial) correlations were statistically significant. They were high as their zero-order counterparts: The average value was $r = .80$, with a range from .82 to 1.00, except again for the only correlation about change in performance (between γ_1 and β_1, $r = -.31$).

Discussion

Findings From the Multilevel Negative Exponential Model

The multilevel analyses at the trial level revealed great variability in skill acquisition both within and between individuals. The intraindividual variability in learning trajectories is evident as the parameter values of the negative exponential function changed across blocks. The interindividual variability is captured by the observed significant random effects in the level of performance and, to a lesser extent, in the rate of acquisition displayed by the participants. Moreover, participants' age and cognitive resources predicted a substantial share of individual differences.

The results show clearly that much progress in PR performance occurred at the beginning of each block. On average, most learning occurred on the first day (especially during Trials 1–25) and the least on the last (third) day (Trials 61–80), which is consistent with the diminishing-returns hypothesis. The greatest learning gains occurred after a day (Blocks 3 and 4, at the beginning of Days 2 and 3, respectively). Indeed, the final performance of the second and third blocks was worse than the initial performance of the third and fourth blocks, respectively. In other words, performance gains occurred not only during practice but also in a hiatus between the blocks as well. The model predicted improvements in absence of direct practice across contiguous blocks. What may be interpreted as consolidation (Brashers-Krug, Shadmehr, & Bizzi, 1996; Karni & Sagi, 1993) was shown only across days, but not after the short 5-min break at Day 1 (Block 2), and diminished in size as learning progressed. Also of interest, even after 80 trials, it appears that at least some participants have not attained their overall upper performance asymptote. Additional learning hence still seems possible, which argues that for at least some of the participants, full consolidation might have occurred even after the experiment ended.

Effects of Age and Cognitive Resources on Learning Parameters

The analytic methods used in the present article allowed quantification of individual differences in acquisition curves and at least a partial explanation of that variability by age and selected cognitive resources. The analyses revealed that deleterious age effects emerged only by the end of the second block and persisted thereafter (Table 3). When participants were novices to the task, relations to chronological age, if present, were collinear with the measures of cognitive resources included in this study except for the beneficial effect on learning in Block 1. In an earlier analysis, we have shown that during the first rapid stage of motor skill learning, the effect of age on performance may be mediated by cognitive and brain resources (Raz et al., 2000). During the second phase, this mediation diminishes, so that the unique effect of age emerges. Our results hence suggest that upper limits of age-related differences in perceptual–motor skills are not alleviated by practice. If anything, they appear to acquire greater prominence once the effect of factors that govern acquisition recedes. It follows that development of expertise may accentuate age effects rather than attenuate them (cf. Brehmer, Li, Müller, von Oertzen, & Lindenberger, 2007). However, at the novice level, older individuals have a higher learning rate. These considerations call for a stronger reliance on experimental designs with a sufficiently large number of trials to allow for attaining close-to-maximal performance (cf. the testing-the-limits paradigm; Kliegl & Baltes, 1987).

We have previously demonstrated that differences in cognitive resources indexed by SR and SJS account for a significant portion of variability in PR performance (Kennedy et al., 2008). The analyses presented here shed light on the way that contribution changes in the process of acquisition. The processes and resources reflected in SR score explained a significant proportion of variance on all blocks except the last, whereas the other nonverbal WM task, the SJS, predicted performance only at the last block (cf. Table 3). The differences in effect of various WM tasks on PR performance may stem from the differences in basic processing ingredients that constitute each of those complex tasks. The two verbal WM tasks, LS and CS, call for manipulation of word and number strings according to rules of grammar and arithmetic, and thus, they are unlikely to overlap with the motor and visual–spatial demands of the PR task. The SR and the SJS tasks call for mental imagery, and whereas the latter is also contaminated by some verbal label processing, the former requires purely spatial manipulations of images for attaining a correct solution. Thus, we can speculate that in the process of acquisition of the PR skill, persons with better ability to manipulate SR had a significant advantage. This is not evident on the last block when asymptotic or quasi-asymptotic levels of performance were attained. It is unclear why the last block showed the effect of a less complex size judgment task. In sum, PR skill acquisition is probably predicated on intact specific resources, namely spatial and mental imagery, and general WM resources that are common to all four tasks employed in this study played no role in the acquisition process.

Performance on the verbal WM and the executive function tasks was unrelated to the level of skill or the course of its acquisition. Although verbal WM is often considered a highly relevant cognitive resource in everyday functioning, its effects in this specific motor skill acquisition were null, probably because the cognitive and the motor tasks are very different in nature and because the PR task is not a good indicator of everyday functioning.

Additional analyses revealed that whereas age and WM together explained on average about 22.33% of the variance in learning parameters, the unique contribution of cognitive resources, in particular nonverbal WM (5.66%), was comparable to that of age (4.67%; Appendix, Note 3). These results are consistent with the general observation that correlates of skill performance change in the course of practice, presumably reflecting shifts in the underlying mechanisms (Ackerman, 1988; Ackerman & Cianciolo, 2000). Such shifts can be interpreted as a transition between an initial fast and a final slow stage of the learning process (Karni & Bertini, 1997; Karni & Sagi, 1993), accompanied by a diminishing contribution of effortful cognitive processes (Voelcker-Rehage, 2008). Nonetheless, the mechanisms underlying stage differentiation in skill acquisition and age differences therein remain unclear, and there is a hope that they can be clarified by discovery of the relevant brain correlates. Differential engagement of brain circuits at early and late learning has been observed (Doyon et al., 2003), and some of the age differences in skill acquisition may stem from variable degrees of shrinkage in the relevant striatal and cerebellar structures (Kennedy & Raz, 2005; Raz et al., 2000).

Generalities of Learning Features Across All Trials

Both analyses, with and without predictors, revealed that individual differences in level of performance parameters were quite stable. The two parameters describing level of performance (α and β) correlated positively and highly, indicating that individuals who performed well at the beginning of the experiment tended to do so all along.

In contrast, individual differences in the rate of acquisition were more elusive and difficult to estimate. Recent simulation studies showed that detection of individual differences in the rate of change requires significantly greater statistical power than is sufficient for discovering individual differences in level of performance (Hertzog, Lindenberger, Ghisletta, & Oertzen, 2006; Hertzog, Oertzen, Ghisletta, & Lindenberger, 2008). Hence, further elucidation of this issue will probably require larger samples.

Study Limitations

The results reported here should be interpreted in the context of the limitations of this study. First, several potentially important covariates of PR performance, such as perceptual speed, have not been assessed. Our operationalization of cognitive resources could have been more comprehensive. Second, although PR is a widely used task, the results obtained here may be specific to the combination of perceptual and motor skills assessed by it and not necessarily generalizable across other perceptual, motor, or cognitive skills. Finally, to take full advantage of the analytic opportunities offered by the multilevel analytic approach, samples larger than the current $N = 102$ are necessary. Although the current sample is not large we could estimate the parameters of the multilevel negative exponential model because the participants had been assessed on 80 occasions (for a total of almost 8,000 data points). Thus, we did not encounter the typical computation problems associated with small sample sizes, although a few estimates were out of bounds. Indeed, in longitudinal analyses, the lack of precision due to small sample sizes can be partially compensated by the density of the longitudinal measurements (Singer & Willett, 2003). We suggest that future studies on skill learning be planned with similarly large or larger samples and a high number of trials.

Finally, the participants of this study were highly educated healthy adults who resided independently in an urban setting. They had no history of neurological, medical, and psychiatric conditions nor sensory or motor impairments. Thus, the generalizability of the findings to the general population is limited. From the perspective of aging research, this sample provides the best-case scenario of successful aging uncomplicated by many debilitating conditions that accompany common aging.

Conclusions

Our findings lead to two conclusions. First, at the individual level, four blocks of 20 trials were not necessary to identify interindividual differences in learning parameters. Indeed, such differences were very stable throughout testing (cf. across-block correlations presented in Table 4). Second, we conclude that at the sample level, learning occurred throughout the whole study with dramatic gains (cf. fixed effects of Tables 1 and 2 and the sample trajectories in Figure 1). We believe that those findings support the notion proposed by Karni and his colleagues that learning evolves in stages, with different processes being more prominent than others at each stage, and their conjecture that perceptual experiences may trigger neural changes that take several hours to become fully functional (i.e., consolidation). The representational changes in the striatum, cerebellum, and the associated motor cortical regions (cf. Doyon et al., 2003; Raz et al., 2000) may thus occur at a slower rate in old age than they do in younger ages. Had we limited the design of our study to the first block only or had we not performed the trial-by-trial analysis, we would be unable to draw this potentially important conclusion.

This study applies a multilevel negative exponential model to testing hypotheses about the structure of skill acquisition process and age-related differences therein. The multilevel methods exhibit several advantages. The most important benefits of this approach were the ability to reveal statistically testable heterogeneity of the acquisition trajectories, to analyze the stability across the experiment of this heterogeneity in learning, to provide evidence for learning consolidation across the blocks, and to show differential contributions of cognitive variables across the learning process.

The findings reported here also reinforce the need for fine-grain analyses of trial-by-trial behavioral changes that are difficult to examine, and even more difficult to interpret, with more traditional analytical methods. Learning research may stands to benefit from the application of MLMs to trial-by-trial data, especially if the number of repeated exposures is high enough to allow participants to reach asymptotic performance. Given the ease of access to appropriate computational resources and relevant software, we hope that the analytical methods demonstrated in this article will find wider acceptance in skill acquisition research and that future designs of learning experiments will include large number of trials on a large number of participants.

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Supplementary Material

Supplementary material can be found at: http://psychsocgerontology.oxfordjournals.org/

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Appendix

1. An anonymous reviewer noted that the data could also be conceived on a more refined hierarchy, such as trials nested within blocks nested within days nested within participants. We adopted a two-level hierarchy of trials within participants because (a) blocks and days are almost completely collinear (only on Day 1 was there more than one block) and (b) with only three (days) or four (blocks) units per level, it is not advised to insert an additional level of analysis in the MLM (Goldstein, 1995). Moreover, for the theoretical reasons listed before and in accordance with the inspection of the trajectories (i.e., Figure 1), we opted to fit the negative exponential model to each block separately, which allowed concluding about the evolution in time (across blocks) of the model's parameters.

2. Under certain conditions, such as those offered here, multilevel and structural equation models are equivalent (McArdle & Hamagami, 1996; Rovine & Molenaar, 2000). Because of practical programming features, we opted for the structural equation modeling implementation rather than MLMs (cf. Ghisletta & Lindenberger, 2004).

3. These results cannot be due to multicollinearity issues because the four WM tasks correlated between 0.47 and 0.61, whereas the executive function (number of persevera-tive errors) correlated between −0.42 and −0.36 with them. Finally, age correlated between −0.52 and −0.24 with the span tasks and 0.50 with the executive function task.